Diffusion of web technologies and practices

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DOI:
10.1016/j.techfore.2015.04.011

Diffusion of web technologies and practices: a longitudinal study

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Acknowledgement: This research was partly funded by the Newcastle Institute for Social Renewal.

Diffusion of web technologies and practices: a longitudinal study

Abstract

Our research objective was to undertake a longitudinally study of how technologies and practices used in web development diffuse over time and whether the diffusion patterns are affected by the regions or the industries in which they take place. The diffusion of web technologies is of interest as, they are highly visible and accessible across the globe and industries by their very nature, which makes it possible to potential adopters to trial them and experience first-hand their relative advantage, compatibility and complexity. Three different cases were chosen, in order to test our hypotheses based on the Diffusion of Innovations Theory. A system was built to collect data using the Wayback Machine. The data collected covered a period of 13 years. Our findings suggest that web innovations may diffuse differently when compared to each other, but also when regions and sectors are considered. Beyond testing the ecological validity of Diffusion of Innovations Theory in web-related technologies, our findings have practical implications which can inform the diffusion of technologies and standards.

Keywords: web technologies, diffusion of innovations, geographical diffusion, sectorial diffusion, Wayback Machine

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1 Introduction

The World Wide Web (or web for short) has become a major part of our daily lives, with millions of users finding their way to web sites using their browsers. By the end of 2014 the number of Internet users globally was expected to reach almost 3 billion (up from about 1 billion in 2005), with penetration standing at 40% globally (but with only 32% in developing countries vs. the 78% in developed ones) [1]. In the early days, developers often felt obliged to indicate that their web sites were still under construction by posting road construction signs on their pages. Over time this practice became less popular as developers realised that web sites are never finalised and that they are continuously evolving. New web standards and technologies, web browser capabilities, design trends, different types of devices and the ever improving Internet infrastructure fuelled web site change as stakeholders aspired to follow relevant innovations and remain competitive. Comparing a web site with a version dating only a few years ago can often highlight how much web developing practices have advanced over time. Understanding web site change and the underlying diffusion of web technologies is important both theoretically and practically. On one hand, it is of interest to study how innovations are propagated on a regional, but also global stage, while on the other the impact that the Internet has had on all aspects of our lives renders any insights of great practical importance for future developments.

Although considerable commentary exists on the paths of Internet development, there is little longitudinal research into patterns of web site change [2](p.180) Web site change can be studied from two key vantage points. The first one is a micro approach revolving around the web site itself (e.g. [3, 4]). The alternative macro approach is to examine changes in a group of web sites, focusing on specific communities of practice, e.g. geographical or based on specific industries, or even on the web itself as a whole, by examining the underlying technologies. The second approach is more suited for studying diffusion patterns, especially methodologically, due to the very nature of the technologies of interest, which makes it possible to collect the required data programmatically. Based on the above, this paper's research objective is to study how technologies and practices used in web developing diffuse over time and whether the diffusion patterns are affected by the regions or the industries in which they take place. In doing so we firstly contribute to the literature by considering the diffusion of web technologies themselves, as opposed to the diffusion of the Internet and its penetration [5-8] or the adoption of the technologies, typically with a focus on the application, at the organisational level [9-11]. Instead of just treating the Internet or the web as unified general purpose technologies [12] our study aims to close the gap between these two bodies of literature by examining the underlying technologies that give rise to our Internet and web experiences. Secondly, given that web technologies are by their very nature visible across the globe [13-16] and different industries [17], one could expect that potential adopters can trial them and experience first-hand their relative advantage, compatibility and complexity. In turn, one may have expected that the diffusion of web-development technologies would proceed in a similar manner. However, in practice this is not what our evidence suggests, as we found variations in the diffusion process. Of course, diffusion does not take place in a vacuum, but within market systems of different attributes and characteristics. Still, the differences observed for rather basic web development blocks that revolved around web standards offer valuable insights in terms of the fit of the models tested and potential managerial implications when it comes to launching new web-based technologies or even to how standards propagate across the web. Thirdly, methodologically, our contribution stems from using the Wayback machine to collect and analyse data programmatically over a period of 13 years.

The paper will continue by presenting the relevant literature, before proceeding to discuss the methodology adopted. It will then present the results of the analysis and discuss these in the context of the research objectives set and the existing academic literature. The paper will conclude by outlining ways of extending this work and future research avenues.

2 Literature Review

Innovation has been defined as "*the generation, development, and adaptation of novel ideas on the part of the firm*" [18], which, from an IT perspective, may refer to a new practice or operational idea [19, 20]. As ICT can affect firm productivity [21, 22], not surprisingly there are many studies that have examined ICT innovation adoption, with various theories being tested [22, 23]. Theories may consider different units of analysis, typically the user, the firm or the market/innovation [24]. As the focus of our work is the organisational diffusion of web technologies as expressed by their web site adopting and implementing such technologies, we turn our focus to the firm-level, grounding our work on Roger's Diffusion of Innovation Theory (DOI) [17]. In the sections following we present the main tenets of DOI and formulate hypotheses revolving around them to perform longitudinal tests.

2.1 Patterns of technology diffusion

Rogers [17] (p.5) defined diffusion as "*the process by which an innovation is communicated through certain channels over time among members of a social system*". In the context of DOI, an innovation is "*an idea, practice or object that is perceived as, but not necessarily, new by the individual or any other unit of adoption*" [17] (p.12). Innovations are not adopted by all in the same way. Innovativeness, i.e. the degree to which an individual is relatively earlier than other members of the social system in adopting an innovation, can segment the social system into 5 adopted categories, namely innovators, early adopters, early majority, late majority and laggards. When the number of individuals adopting an innovation is plotted on a cumulative frequency basis over time, for a successful innovation that spreads across almost all of the potential adopters in a social system, the resulting distribution is an S-shaped curve. The exact shape and location of each S-curve is innovation-specific and system-specific, describing the diffusion of a particular new idea among the member units of a specific system [17](p.275). For instance, the seminal work of Ryan and Gross [25], which focused on the diffusion of hybrid seed corn among farmers in two communities in Iowa, demonstrated that the diffusion of corn follows an S-shaped curve with a small number of adopters at the beginning of the curve and then a gradual increase of adopters over time. Various media, information and communications technologies have been found to diffuse in a similar manner [26-28]. More specifically, when it comes to web technologies, Chen [9] analysed the adoption of e-business standards such as XML and web services. He found that both XML and web services follow an S-shaped diffusion pattern. Teng et al. [29] assessed 20 different information technologies and their diffusion patterns with respect to models that were subject to internal and external influence. They found evidence that models of diffusion due to imitation, such as the logistic S-curve, perform better than other more elaborate models. The S-shape is found in the literature to be appropriate for a variety of alternative assumptions about adoption mechanisms, e.g., Hall and Khan [30] argue that both the adopter heterogeneity and the learning/epidemic model lead to S-curves in innovation diffusion. Geroski [31] also observes that both different theoretical models of technology diffusion and empirical studies lead to the conclusion that diffusion follows an S-shaped pattern.

For our study we selected the internal influence model (partly due to the longitudinal nature of the study and the methodology adopted, as discussed later in the paper), as represented by the logistic curve, which is based on the assumption that diffusion occurs only through contacts among members of the social system, proposing that:

H1: Web technologies diffuse following an S-shaped pattern.

In DOI, the rate of adoption is defined as "*the relative speed with which an innovation adopted by members of the social system*" [17] (p. 221), which may be affected by a number of the innovation's characteristics, such as its relative advantage, its compatibility, its complexity, the ability to trial and observe it. Relative advantage refers to the degree to which an innovation is perceived as being better than its alternatives. Compatibility defines the alignment of the new innovation with existing values, past experiences and the needs of those considering adopting it. Complexity refers to how difficult the innovation is to understand and use, while trialability is the extent to which an innovation can be experimented with before being adopted. Finally, observability refers to the degree to which the results are visible to others. If an innovation is perceived as having high degrees of the above, it is expected to be adopted more quickly and will consequently diffuse faster. Additional factors that may affect the adoption rate may include the type of innovation-decision, the nature of communication channels diffusing the innovation, and the nature of the social system in which the innovation is diffusing and the extent of change agents' promotion efforts (see Rogers [17] for a full discussion on these points). Others have also found similar and other factors that affect the diffusion of innovations, including the innovation's characteristics [32-35], organisational characteristics [36], individual characteristics of the individual adopting the innovation [37], internal management support [34] and the external environment [38, 39]. When looking at technology diffusion rates for various media and communications technologies since their year of inception (e.g., the cell phone, Internet and television), one finds that the rate of diffusion differs from technology to technology. The telephone took close to 75 years to reach 50 million users worldwide while it took only 4 years for the Internet to reach the same number [26]. Kim and Kim [40] also found differences in the diffusion of technologies in their study of the penetration rates of circuit versus packet-based innovations. They found that packet-based innovations diffused more quickly than circuit-based innovations as a result of internal and external influences. Of course, undertaking a precise comparison of diffusion among different technologies is rather challenging as diffusion does not happen in a vacuum and it is not possible to control for all factors that may affect the process.

The diffusion of innovation theory also highlights that, within the rate of adoption, there is a point where the innovation reaches critical mass. This is a point in time within the adoption curve at which the adoption of the innovation is self-sustaining [17]. The concept of critical mass is essential for new communication technologies [41]. According to Rogers [17], "*the interactive quality of new communication technologies creates interdependence among the adopters in a system*" (p. 343). A critical mass of individuals must adopt an interactive communication technology before it is useful for the average individual in the system. With each additional adopter, the usefulness of an interactive communication technology increases for all adopters. The rate of adoption is very slow until a critical mass is reached, which then accelerates the rate of adoption [41]. According to Mahler and Rogers [41] (p.720), telecommunication innovations with strong network externalities or "*a quality of certain goods and services such that they become more valuable to a user as the number of users increases*" will have a more pronounced critical mass in their rate of adoption.

The critical mass point of the diffusion process of technologies may differ from technology to technology, e.g., as found in a study on the adoption of 12 telecommunications services by 392 German banks [41]. The rate of adoption for innovations such as the fax, electronic mail, and videoconferencing displayed a relatively strong critical mass in comparison to other telecommunications innovations, such as mobile telephones and voice mail. Kim and Kim [40] found that packet-based innovations reached their critical point at 4.7 years while it took 17 years for circuit-based technology to reach its critical mass point. In another study examining the diffusion of products, Tellis et al. [42] found that the time it took to reach the critical mass point for kitchen and laundry products was 7.5 years, compared to only 2 years for information and entertainment products.

As there has been little empirical evidence on the diffusion of web technologies and based on the above, the following hypotheses are put forward:

H2: The rate at which web technologies diffuse differs from technology to technology.

H3: The (level of) critical mass point of the diffusion process of web technologies differs from technology to technology.

2.2 Patterns of technology diffusion by region

Early research on ICTs suggested that geography did not matter, due to the effect of ICTs on the dispersion of economic activities. Scholars from this perspective argued that ICTs have an anti-spatial nature [43] and geographical proximity is less important than originally suggested. For instance, Cairncross [44] discussed the "*death of distance",* explaining that distance was no longer a factor in how business was conducted, and Friedman [45] argued that "*the world is flat*", due to the vast penetration of ICTs. However, more recently it has been recognised that geography still matters for ICTs as they are still highly spatial in nature, as proven by empirical research [13-16].

The importance of geography has also been recognised by the diffusion literature. There are various studies analysing the role of geography in patterns of technology diffusion, suggesting that the rate at which technologies diffuse is different from one geographical region to another. This is a result of country differences in terms of geographical, socio-economic, demographic and cultural characteristics, which influence how a product or service diffuses over time [46, 47]. Differences in the rate of technology diffusion from one geographical region to another also occur because of the "*lead-lag effect*", which is based on when the innovation is introduced [48]. Countries that introduce a given innovation later show a faster diffusion process as "*the change in the design and quality of products and the availability of more advanced media vehicles and communication systems over time may considerably influence the rate of adoption of new products in countries where the products are introduced later*" [46] (p.49). Potential adopters learn about product benefits from prior adopters in other countries [49, 50].

Empirical studies analysing the patterns of technology diffusion also demonstrate that the rate at which technologies diffuse is different from one geographical region to another. Some empirical studies highlight the effect of country differences, such as in socio-economic, demographic and cultural characteristics on how a product or service has diffused over time. For instance, Mahajan & Muller [51] evaluated the diffusion of videocassette recorders among the member and non-member nations of the European Union (EU). They found that the videocassette recorder diffused differently across member and non-member nations as a result of EU differences in economic, social and cultural aspects and consumer preferences and choices [47]**.** Caselli and Coleman [52] analysed the diffusion of computers across 155 countries, finding differences as a result of varied levels of human capital, manufacturing trade openness, property rights protection and the role of the size of government. In a study on the diffusion of wireless communications across 64 countries, Sundqvist et al. [53] found differences in the diffusion process based on cultural differences, while Vicente and Lopez [54] discovered differences in the patterns of ICT diffusion across EU countries which were a direct result of socio-economic factors. Zhu et al. [55] analysed e-business diffusion across 10 developing and developed countries at the firm level. They found differences in the diffusion of e-business across developed and developing countries as a result of the different economic and regulatory environments. Other empirical studies have examined the effect of the lead-lag effect, which influences how a product or service diffuses over time. For example, Takada and Jain [46] examined the diffusion process of consumer durable products in 4 Pacific Rim countries, accounting for the lead-lag effect. They concluded that there were differences in the diffusion patterns across countries whereby products introduced later into one country lead to an accelerated diffusion process. Dekimpe et al. [56] (p.58) also found empirical evidence of "*international contagion effects*" in their study of the international diffusion of digital telephony. The results of their study suggest that the more countries that adopt an innovation, the higher the chances that the innovation will also be embraced by other countries.

The time to reach the critical mass point of the diffusion process of technologies may also be different from one geographical region to another. Tellis et al. [42] analysed the variation in time to take-off of 10 new consumer durables across 16 European countries. They found that the diffusion of new products differs dramatically among countries, which is a direct result of national culture. They also concluded that the probability of diffusion of a new product in a country was higher if that product had already reached critical mass in neighbouring countries. Frank [57] examined the rate of mobile telephone diffusion in fifteen countries of the EU, finding differences between the diffusion processes, with mobile phones diffusing faster across northern Europe than southern Europe. In another study, Forman et al. [58] concluded that Internet adoption for firms with more than 100 employees was faster in smaller cities.

Despite the empirical evidence suggesting that ICT technologies may diffuse in different ways across geographical regions (and sectors, as discussed in the next section), this may not apply for the particular web technologies under study. Past research indicates that relative advantage, compatibility, trialability, observability and complexity are the most important characteristics of innovations when it comes to explaining the rate of adoption [17] (p.16). Given the clear relative advantage of the technologies and practices under study vs. the existing approaches (especially when it comes to agreed standards that are supported by the most popular web browsers), the high compatibility and low complexity of the technologies considered, the ample scope for trials and the global nature of the Internet, which made it possible to observe their effect easily, it might be expected that each of these technologies and practices would have diffused in a similar manner across a number of geographical regions and sectors:

H4: The rate at which a web technology diffuses is the same from one geographical region to another.

H5: The (level of) critical mass point of the diffusion process of a web technology is the same from one geographical region to another.

2.3 Patterns of technology diffusion by industry

Technology spreads among companies in an industry in a diffusion process that is similar to the way it diffuses among the individuals in a community or some other system [17]. "*The diffusion pattern at the industry level is the outcome of the distribution of individual firm adoption decisions*" [59] (p. 3). The rate at which a technology diffuses may be different from one industry to another. This is because certain sectors (e.g. telecommunications and financial services) lead in the adoption of certain technologies (e.g. IT innovations) [60]. According to Day and Herbig [61], "*the greater the* *essentiality of an innovation within a particular industry, the higher the likelihood and quicker the adoption of an innovation by a firm within that industry*" (p.264). This essentiality refers to the importance of an innovation to the continued operation of a firm. The rate at which a technology then diffuses may also be different from one industry to another because of the characteristics of a specific industry. As noted in the previous section, the interactive quality of new communication technologies creates interdependence among the adopters in a system and is affected by network externalities. This suggests that the rate of diffusion for new communication technologies may be slow at first, but then speed up once a critical mass has been reached as more users adopt a technology.

While there is some evidence showing that the sector in which a firm operates has little influence on information systems innovation adoption [62], most empirical studies analysing adoption patterns demonstrate that a firm is influenced by the industry in which the firm operates [63]. In a study on electronic data interchange (EDI) use in 4 organisations across different industries, Crook and Kumar [64] examined how and why different factors impact EDI use. They found inter-industry differences between the use of EDI, which was a result of industry experience, the nature of suppliers, and the nature of customers within a given industry. Grover [34] analysed the adoption of customer-based inter-organisational systems (CIOS) accounting for various factors, including the industry sector the firm was based within. In relation to the influence of industry, he found that organisations in industries where the CIOS concept is prevalent tend to be more likely to adopt. Additionally, CIOS tended to be adopted in industries where customers have strong buying power and where there is high competition among firms.

Similarly, empirical studies focused on technology diffusion demonstrate that diffusion patterns may be different from one industry to another. The broader ICT literature indicates that the rate of ICT diffusions is faster in the service sector (e.g. finance, banking and business services) [65], which are more dependent on this type of technology to function. For instance, Zmud [66] examined the diffusion of six modem software practices (MSP) into 47 software development groups (e.g. aero-space related organisations and non-defence federal agency organisations). He found inter-industry differences in the rate of diffusion of MSP. The aerospace industry made greater use of MSP than the non-defence federal agency industry. Romeo [67] analysed the diffusion of machine tools across 10 industries. Based on a survey of 152 firms, he discovered large inter-industry differences in the rate of diffusion of machine tools as well as differences in the length of time firms within an industry adopted machine tools. Romeo [67] also concluded that machine tools spread more rapidly in less concentrated industries than in large scale industries. In an empirical investigation on the percentage of firms within an industry adopting laptops, Gatignon and Robertson [68] also found differences between industries. They concluded that the diffusion process was maximised in more concentrated industries and that the less the competitive price intensity the more likely the diffusion of technologies in that specific industry. The former is because firms in more concentrated industries use innovations as a competitive tool, while the latter is because the lack of price pressure frees resources for potential adoption of innovations (ibid).

Based on the above literature and the arguments put forward in the previous section about the nature of web technologies we propose the hypotheses below:

H6: The rate at which a web technology diffuses is the same from one industry to another.

H7: The (level of) critical mass point of the diffusion process of a web technology is the same from one industry to another.

3 Methodology

3.1 Measuring diffusion using the Wayback Machine

Our system was built with PHP and mySQL, using freely available libraries. The system uses a three step analysis, following a similar analytical approach to the one used by Broder et al. [69] for determining the syntactic similarity of documents. In our case, there was less emphasis on scaling the algorithm as we were only interested in the comparison of a relatively small number of web sites and documents. The speed of retrieving and analysing pages depended on the available hardware resources and Internet connection speed. In the first step, the data collector retrieves web pages from the Internet Archive, and more specifically the Wayback Machine (http://archive.org/web/web.php), which makes it possible to browse through the history of over 435 billion web pages. A number of studies have examined the use of the Wayback Machine as a data repository for archiving or have utilised it while studying web sites [2, 70-73]. Despite its limitations (e.g. it is not searchable by keywords or text in the manner of a general search engine, or data such as the gopher content is missing [74], while web sites can request to be excluded, limiting the archives' comprehensiveness [75]), the Wayback Machine has been shown to offer content validity for three measures, namely website content, website age, and number of updates as well as predictive, nomological, and convergent validity for website age and number of website updates [75]. Our system retrieves and stores the copy of the home page for each web site requested in a database, enabling further analysis. The Wayback Machine archive goes back to the mid-90's. However, not all sites dated back to that time and nor had all sites been consistently archived from the beginning. Given that before 2000 data availability is often scarce, pages were requested from January 2000 to December 2012 inclusive. Pages were filtered using keywords to detect specific errors (e.g. 404, i.e. file not found or Wayback-related errors) before being inserted in the database. A web site can have up to 156 (13 years x 12 months) records in our database. When requesting a page, the Wayback machine expects a date as input and returns the closest entry to that date. Our system input the 15th of each month, in order to maximise the chance of the returned page falling in the same month as the data entered. If not, it discarded the returned page. Comparisons were restricted to the home page as this is a key section for every web site (and also in order to ensure a minimum of consistency). Web sites were organised into groups (geographically or based on industry sectors). To measure the diffusion of web technologies and trends, we scanned each document's source code for specific keywords, setting the adoption value for that instance to 1, if the technology was used, and to 0, if it was not.

3.2 Selecting the technologies to study

We opted to study the diffusion of 2 open web technologies, namely Cascading Style Sheets (CSS) and JavaScript, and one proprietary, namely Adobe Flash, that appeared around the mid-90's. This makes it possible to compare their diffusion over the same time period. CSS are used to describe the presentation semantics. They were introduced in 1996 and over time became the standard method for separating content from presentation. JavaScript, which first appeared in 1995, is a client side scripting language typically adopted in order to make web pages more interactive. Adobe Flash aims to deliver rich multimedia content (including video) across platforms. It has gone through various developmental phases and market positioning, historically enjoying very high user adoption rates. We also scanned for links to social networking sites such as Facebook, Twitter and YouTube. As social networking became more popular, more web sites started linking to these networks from their home pages, often integrating features that the networks made available (e.g. liking or commenting on posts, embedding content such as YouTube, or signing in to third-party services by using Facebook and Twitter credentials). Consequently, although social networking does not refer to a specific technology as such, it is still a significant web developing practice that can be used as a proxy for corporate adoption of social media. Including social networking sites in the data collection process also made it possible to examine visually whether our methodology was working as expected. In the final step, we exported the data for further analysis. Given that we are not interested in individual sites, but groups, monthly average scores for each sample were calculated, which resulted in a number of time series (as plotted in Figures 1, 2 and 3; in all figures CSS stands for Cascading Style Sheets, Flash for Adobe Flash, JS for JavaScript, Tw for Twitter, Fb for Facebook and finally Yt for YouTube).

PLEASE INSERT FIGURES 1-3

3.3 Model used

To assess whether the diffusion process follows an S-shaped curve, we fit the logistic function into the time series representing the adoption level for each technology. The logistic function has been widely used in the technology diffusion literature since Griliches [76], and we apply the following functional form, as recommended by Beck et al. [77]:

$$S_t = \frac{\gamma}{1+\exp(-\beta(t-\tau))} \tag{1}$$

where S_t denotes the level of technology adoption at time t (in our case, $0 \leq S_t \leq 1$), t denotes time, and $\exp(.)$ denotes the exponential function. γ, β, and τ are parameters to be estimated that govern the shape and location of the logistic curve. Specifically, the function S_t is symmetric around the inflection point at t= τ, for which it equals half of its saturation level γ. At t= τ, the curvature changes from convex to concave, meaning that prior to (beyond) that point the growth rate of adoption increases (declines) over time. There is no single figure to describe the growth/diffusion rate of innovation, as a visual examination of the shape of the S-curve will demonstrate that the rate (graphically: the slope of the curve) changes over time. The common approach in the literature to obtain a single figure representing the growth/diffusion speed of the whole process is to observe its highest value in the time frame analysed: this can be shown to equal $\beta/2$, observed at inflection at time τ [77][1]. For the sake of coherence, we report the values of β.[2]

The logistic function presented above will make it possible to test hypotheses *H1-H7* in the following way. Firstly, to test whether the adoption process of any given technology follows an S-pattern, the fit of function (1) to the data can be assessed. As Comin et al. [79] notice, the necessary condition for the data to be described as featuring an S-shape is for it to be possible for the

[1] The meaning of those parameters is not just assumed, but can be shown analytically to hold. We do not include this proof to conserve space, but it is available on request.

[2] Meyer et al. [78] offer a model as well as an accompanying software to decompose growth and diffusion processes into S-shaped logistic elements, an approach they term “loglet analysis”.

parameters of the logistic function to be estimated. Hence, if function (1) cannot be fitted to the data describing a given technology's adoption pattern, it can be concluded that this process does not follow an S-shaped curve. To operationalise this condition, we will conclude that a process follows an S-shaped pattern if all parameters, γ, β, and τ, are individually statistically significant. Additionally, even if parameter estimates can be obtained, the measure of the goodness of fit, R^2, is not appropriate to assess the fit of the logistic function, as processes following S-shaped patterns are largely driven by positive trends and high values of R^2 will mirror good fit of the function to the trend, rather than to the actual data. Hence, Comin et al. [79] advocate the analysis of significance, signs, magnitudes, and meaning of the estimated parameters (γ, β, and τ) as a way of assessing whether the observed process follows the S pattern given by the logistic function. Secondly, to assess the speed of technological diffusion, two measures can be used: the estimated maximum growth rate, as captured by the parameter β, and the estimated time when half of the saturation level is reached, as measured by τ.

Thirdly, no consensus seems to exist in the literature on how to measure the critical mass (see, e.g., Chandrasekaran and Tellis, [80], for a review). In addition, two aspects of the critical mass can be distinguished among, the timing (i.e., when does a product/technology achieve its critical mass) and the level (i.e., what is the cumulated adoption level beyond which the process is sustainable). The timing aspect is captured by our parameter τ: regardless of how the critical mass level is defined, a process with lower τ value will reach this level later. As for the level of critical mass, the estimated saturation level γ will be used as a proxy: the technology reaches a sustainable level and its adoption growth rate starts to decrease when the overall adoption level surpasses the inflection point of $\gamma/2$ at time τ.[3]

[3] Alternatively, Ferreira and Lee [81] employ the concept of Moore's chasm [80]: the gap between early adopters and the early majority, which they operationalise by employing a threshold of 16% of total users (i.e., of the saturation level), in accordance with Rogers's [17] original proposition. However, any threshold value seems to be arbitrary. Assuming the same functional form of the diffusion process across different cases, timing and level are two sides of the same coin: a difference (between two innovation processes) in timing of reaching any arbitrarily chosen level (5%, 16%, 50%, etc.) will indicate a difference in the time when the critical

An alternative modelling approach would be to fit a different function to each diffusion series (for each technology/region/industry), to allow for the best fit of each empirical model. However, by employing the same functional form / model across all technologies/regions/industries, we obtain results which are directly comparable with each other. Hence, differences in parameter values are easily attributable to differences in diffusion characteristics across series, rather than being confused with those generated by differences in functional forms used.

Our choice of the simple logistic curve to capture the diffusion dynamic is motivated by several factors. Firstly, it should be noted that our main aim is to obtain a model with best in-sample fit, and with parameters which are straightforward to interpret and link as directly as possible to our hypotheses. Most of the literature, however, is concerned with models' ability to accurately predict future adoption rates [82] and tends to ignore the issue of the interpretability of the model's parameters. Therefore, using those most up-to-date functions with best forecasting ability would not allow us to address our research questions related to in-sample model fit, or to obtain parameter estimates that are meaningful in light of our hypotheses. Secondly, the empirical literature shows that the logistic curve performs well in terms of in-sample model fit as well as forecasting ability. For instance, Meade and Islam [83] investigate 29 models based on variants of artificially created data, with varying features. The simple logistic curve is found to be the best fitting model, regardless of the features of the underlying data, such as the existence of and symmetry around the inflection point. Thirdly, even if the forecasting ability is considered, empirical studies yield strong support for the use of logistic models (e.g. [84-86]). In addition, we analysed our data using the Franses [87] test and the results for the overwhelming majority of cases show that the simple logistic curve is to be preferred over the asymmetric (Gompertz) model, as it fits the data better.[4] Lastly, the parameters of the simple logistic curve, as opposed to many other models, are

mass was reached. That is, if technology A reaches saturation of 5% faster than technology B, it also holds for saturation at any other level (5%, 50%, etc.), assuming the same functional form of their diffusion processes. Hence, any saturation level can be used to assess the differences across technologies/regions/sectors/etc.

[4] Results not reported, but available on request.

directly interpretable in light of our hypotheses, and can be tested for their statistical significance in a straightforward way. The literature also argues in favour of simplicity, transparency, and interpretability [30, 88].

In addition, the literature offers various alternatives to the simple logistic curve where the analysed products/technologies are e.g., competitive or complementary to each other.[5] However, the technologies analysed in this paper are neither complementary nor substitutable to each other, hence fitting models assuming links between technologies would result over-parametrisation and lower efficiency of the estimates, potentially leading to erroneous inference. Models with explicit links among products would be better suited to analyse the nature of those relationships; our research questions focus on the existence and basic features of the S-shaped diffusion processes instead. Hence, we employ the logistic model to each process.

3.4 Sampling

In this paper we selected three different cases to study, to test our hypotheses, which call for a comparison of technologies, sectors and geographical regions. In the first case we examined the adoption of the selected technologies in the Higher Education Sector in the United Kingdom. We select a specific sector and a specific country as a special case to use for comparing the technologies within a more localised environment, as opposed to a representative one of how the technologies diffused overall. Higher Education institutions were early adopters of the Internet and consequently the majority of them were expected to have both considered adopting the selected technologies, but also feature in the Wayback Machine, which was important methodologically. The sample consisted of University and Colleges web sites. The list used was the Universities and Colleges Admissions Service (UCAS) list, as made available on their list of members. The second case examined Higher Education sites across the globe, grouping them by continent (namely, Africa, Asia,

[5] See, e.g., Shocker et al. [89] who review the relevant diffusion literature with a greater focus on how products/technologies can be related to each other, and Peres et al. [48] for a review of diffusion models according to the forces which shape consumer choices, with a special focus on diverse social influences shaping the interdependencies among adopters.

Australia, Europe and North and South America). A list, obtained from http://univ.cc, was manually and programmatically cleaned and filtered, resulting in a list of about 5,800 sites. Then a geographically disproportionate stratified random subset was used for the study. Finally, we compared 4 different sectors in the United Kingdom. Using the database of the Open Directory Project (http://www.dmoz.org/), we compiled a list of advertising and marketing (A&M) companies (services), companies under the agriculture and forestry category (A&F) (services and products), construction and maintenance companies (C&M) (services and products) and finally web designing (WD) companies (IT services). Due to their nature, the advertising and web designing sectors were selected as potential early adopter sectors that had a high interest in and direct involvement with web technologies. The construction and maintenance and agriculture and forestry companies were expected to be more conservative when it came to adopting new practices and to lag behind the other two sectors. Similar to the geographic sampling, a disproportionate stratified random subset was used. A summary of the samples used is tabulated in Table 1. In total, our dataset included 152,199 data points for 2,585 web sites.

PLEASE INSERT TABLE 1

4 Results

The logistic function (1) has been fitted to adoption time series for our three samples. We used the nonlinear least squares procedure and controlled for autocorrelation of residuals, by explicitly modelling them as an autoregressive process, in order to obtain consistent standard errors of parameter estimates.

4.1 Sample 1: Diffusion of Technologies

The results for the data representing UK universities are displayed in Table 2. As can be seen, it was possible to obtain the parameters for all technologies. However, only for Cascading Style Sheets

(CSS) and JavaScript (JS) were all relevant parameters (γ, β, and τ) significant, indicating that the adoption of the remaining technologies does not follow an S pattern as described by equation (1). For CSS, the estimation results suggest that the saturation level γ is 97.81% and the inflection point (half of the saturation level) was achieved in month τ=24 of our sample (December 2002). For JS, the saturation level γ is slightly lower, at 96.51%, although the difference in γ for these two technologies is not significant (p-value of .9550). The value of β, i.e., the maximum adoption speed, for JS is almost half the size of the β value for CSS, but the statistical test shows that this difference is not significant at any conventional significance level either (p-value of 0.1072). Where these two technologies differ significantly, however, is the timing of the inflection point, as measured by τ: the value for JS is only 67.4690, which shows that the inflection point was reached significantly later than by CSS (p-value of 0.0004). Overall, the conclusion is that these two technologies, CSS and JS, introduced at around the same time in our sample, have virtually identical saturation levels, but the adoption speed of CSS was significantly higher than that of JS, at least in the period before half of the saturation level was reached. Social networking may not have been found to follow the S pattern, as it has not had sufficient time to fully converge. We still kept them in Figures 1, 2, and 3 as they provide visual evidence that the methodology is working as expected. It also demonstrated that the adoption of social networking sites is typically coupled and that web developers tend to add them to web pages as a group. In the rest of the analysis we focus on the technologies that were found to follow the S-shape, namely CSS, JavaScript and Flash.

PLEASE INSERT TABLE 2

4.2 Sample 2: Geographical Analysis

Table 3 presents estimation results for data from six regions, as well as global data on the adoption of 6 web technologies. As before, no reliable estimates could be obtained for Facebook (FB), Twitter (TW) and YouTube (YT), suggesting that the adoption pattern of these technologies does not follow a pattern as described by the logistic function (1). However, for CSS, JS and Flash most regions adhere to the logistic process of diffusion, as indicated by largely significant parameters γ, β, and τ.

The saturation level for CSS globally is estimated to be 95.76%, but this figure differs across continents. South America and Africa feature significantly lower estimated saturation levels, at 87.86% and 88.47%, respectively. On the other hand, Europe's estimated saturation level is the highest (γ=1.0005), followed by North America, Australia, and Asia, albeit the latter at 94.81% is not significantly different from the global level. The speed of CSS adoption at inflection point is given by half of β, with this parameter being 0.0438 globally. Again, regional values differ, with the value for Australia being significantly higher and that for Europe significantly lower than the global average. The latter finding is somehow surprising, suggesting a slow adoption rate for Europe; however, this result may have been affected by the fact that the observed adoption rate at the sample's start for Europe was high already; therefore the data did not follow the process required for a good fit of an S-shaped function. Lastly, the timing of inflection, as a measure of adoption speed, also differs significantly across regions, with Africa reaching half of its estimated saturation level significantly later and Asia, Australia, and Europe significantly faster than the global average. All in all, the results show regional differences in the characteristics of CSS adoption.

As for the adoption of JS across regions, data for all regions except North America adheres to the functional form in (1). The global estimated saturation level is even higher than for CSS, at 98.39%, and values differ across regions. However, only for South America is the saturation level significantly different (lower) from the global value. The highest level of γ can be observed for North

America. The speed of JS adoption at inflection point, as measured by (half of) β, is lower than for CSS, and also differs across regions. However, these differences, as compared to the global β, are not significant, with the only exception being Australia, where β is the highest of all regions. On the other hand, adoption speed at inflection is the lowest for Africa and South America. Lastly, the timing of inflection τ for the global data is double the size of that for CSS, at 61.5332, suggesting a slower adoption process for JS as compared to CSS. Europe and Australia seem to have been the fastest adopters of JS, although only the latter is significantly faster than the global market. On the other hand, Africa is the slowest adaptor of JS, and the only region with τ being higher than the global value. In summary, the adoption characteristics for JS differ across countries, but statistical tests show fewer significant regional differences than for CSS.

The adoption patterns for Flash across regions can also be described as S-shaped for all regions except for Australia and North America (for these two exceptions, the parameters of the logistic function are insignificant). The estimated global saturation is much lower than for CSS and JS, at 39.77%, and, again, differs across regions: it is significantly lower for Europe and Africa and significantly higher for Asia and South America. The speed of Flash adoption at inflection point, as measured by (half of β), is higher for Flash than for CSS or JS, but differences across regions are not statistically significant. The time when 50% of the estimated saturation was reached (at t=τ) lies between the estimates for CSS and JS, South America and Asia arriving at that level of adoption significantly faster than the global market, and Europe and Africa lagging behind (the former significantly in the statistical sense, but only at 10% level).

4.3 Sample 3: Sectorial Analysis

The estimation results for four UK sectors: Advertising and Marketing (A&M), Agriculture and Forestry (A&F), Construction and Maintenance (C&M), and Web Design (WD), are presented in Table 4. Again, the logistic curve could not be fitted to data for the three social networks examined. The first three sectors are compared to the last one, web design, as the web design sector could be expected to be at the forefront of adoption of web-related technologies and therefore constitute a good benchmark for the remaining sectors.

The adoption of CSS appears to differ across sectors, with A&M and A&F (but not C&M) showing significantly lower saturation levels than WD. The point estimates for the adoption speed at inflection, β, are very close to each other, and no value is significantly different from the one estimated for WD. However, when adoption speed is measured by examining the time it took to reach half of the saturation level (τ), all three turn out to have been late adopters as compared to WD, with A&F taking more than double the amount of time to reach the inflection point.

When it comes to the adoption of JS, only A&M and WD can be unconditionally described by the S-shaped curve as in (1). The saturation point for A&M is as high as 97.86% but still significantly lower than that of WD. Its slope at inflection is higher, but not significantly so, and its inflection timing is significantly delayed as compared to that of WD. As for C&M, two of its three parameters are significant, hence there is some evidence in favour of the S-curve. Its saturation point is at the very low level of 57.67% and inflection timing is also significantly earlier than for WD.

The data for adoption of Flash fits into the S-shaped pattern of technology adoption for all sectors. A&M and A&F were found to have significantly lower saturation points than that for WD, and all three sectors show significantly lower adoption speeds at inflection than WD. Lastly, A&F and C&M, but not A&M, lagged behind WD significantly when it came to the inflection timing. Overall, the sectorial differences for Flash seem to be substantial.

PLEASE INSERT TABLE 3 & 4

5 Discussion and Concluding Remarks

This paper's research objective was firstly to test the ecological validity of DOI by examining the diffusion of web technologies across a number of cases, geographical regions and sectors from the technological vantage point, secondly to contribute to a technological area in which little empirical evidence exists and thirdly to adopt a new methodological approach that was based on utilising the Wayback machine. Our findings are summarised in Tables 5a and 5b, with "Yes" indicating empirical support for the respective hypothesis (and "No" indicating lack of support), followed by technologies/regions/sectors where supportive evidence was found.

PLEASE INSERT TABLE 5a & 5b

We found evidence that differences in adoption exist, as evidenced by the presence of the technologies on their home pages. For instance, the above resulted in two rather distinctive patterns followed by the open technologies (JS and CSS) and the proprietary one (Flash). This finding links with existing literature, which suggests that the rate at which technologies diffuse differs from technology to technology [40]. The diffusion patterns cannot be explained without considering each technology's contextual factors and key events that may accelerate or decelerate the diffusion processes. For example, although JS and CSS, both open technologies that offered significant advantages, were both introduced at the same time their diffusion rate was different as the JS diffusion was initially slower than that of CSS, but it then picked up pace. Interestingly, this coincided with the advent of social networking and other similar interactive services that saw JS-based coding frameworks used as a means of adding interactive elements to services that did not require refreshing the entire page. Utilising JS as part of AJAX (Asynchronous JavaScript and XML) effectively redefined the relative advantage of JS by utilising existing standards in a new way. This suggests that when considering diffusion patterns of technologies within fast paced technological environments such as that of the Internet, innovation characteristics can be dynamic in nature and may also need to be examined longitudinally, as they may change significantly over time.

In order to understand diffusion patterns the actors considered should include not just the immediate unit of analysis (in this case the organisation as represented by its web site), but also the end-users and the IT industry that facilitates the interactions between the two parties. For instance in the case of CSS the diffusion pattern that appears to be closely following the S-curve camouflages the struggle of developers to implement an open standard. This was due to web browsers adopting a differential approach on their implementation of CSS, which resulted in rendering the same page different across browsers. As a result, developers had to build separate version of their sites that were optimised for each browser. In turn, the adoption of web browsers and their availability on various operating systems and form factors (e.g. on smart phones, tablets and desktop computers) meant that the adoption of a CSS standard and its intended implementation was dependent on a number of intertwined relationships. This is better demonstrated by considering the case of Flash, which was almost universally present on desktop computers. Still, although it was also initially supported on Android devices, this was not for iOS ones too, leading to a controversial conflict between Adobe and Apple [90]. Later decisions by Adobe and Google related to its development and support had an impact on its future. Our evidence, collected by only looking at the outcome of the adoption decision as captured by our methodology, can only offer insights from one vantage point. A web strategy approach may be useful in appreciating the diffusion patterns across the web ecosystem more effectively [91].

Such contextual differences may also account for the variance found when it comes to the diffusion of open technologies (such as CSS) that should have exhibited, at least in theory, a high relative advantage, compatibility and trialability, and low complexity. The very nature of the web sites, namely being accessible to any user who has access to the Internet, would also imply a high observability. Despite the above, our empirical evidence suggests that there are differences among geographical regions and industries. Although the evidence is not consistent enough to provide concrete evidence for a "*digital diffusion divide*" among them, certain results are in line with expectations (e.g. the relatively quicker adoption in North America and Europe or among companies in the web design sector). These findings diverge from existing studies which suggest that the sector in which a firm operates has little influence on information systems innovation diffusion [62] and support the findings of other studies which suggest that a firm's diffusion patterns are influenced by the industry in which the firm operates [63]. The findings also support existing literature which suggests that the rate at which technologies diffuse is different from one geographical region to another [51]. A multi-perspective framework like the one proposed by Tornatzky and Fleischer [92] that adds an organisational (resources and the characteristics of the firm) and environmental (the arena in which a firm conducts its business) context to the technological one could capture the adoption and in turn the diffusion processes more holistically, albeit rendering a longitudinal approach more challenging.

5.1 Future research

Future research could combine the macro and micro views in the same study, which would simultaneously examine the longitudinal diffusion patterns with the underlying decisions, despite the latter being potentially affected by time-bias. Such a study could take into consideration the organisational characteristics and how these may influence the adoption decisions as time goes by. Similarly, a cross-sectional study examining the factors affecting the diffusion of web technologies and practices by organisations in detail would be of interest. Also a deeper data collection that would include multiple pages for each site in the analysis could offer a more representative view of how technologies diffuse across a web site and not just whether they feature on its home page. Finally, despite the popularity and wide-spread use of social media, it is worth remembering that this is a relatively new phenomenon that is not fully captured in our data collection. Future studies could revisit this once sufficient time has elapsed for the diffusion patterns to converge.

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Figure 1: Diffusion patterns for Sample 1

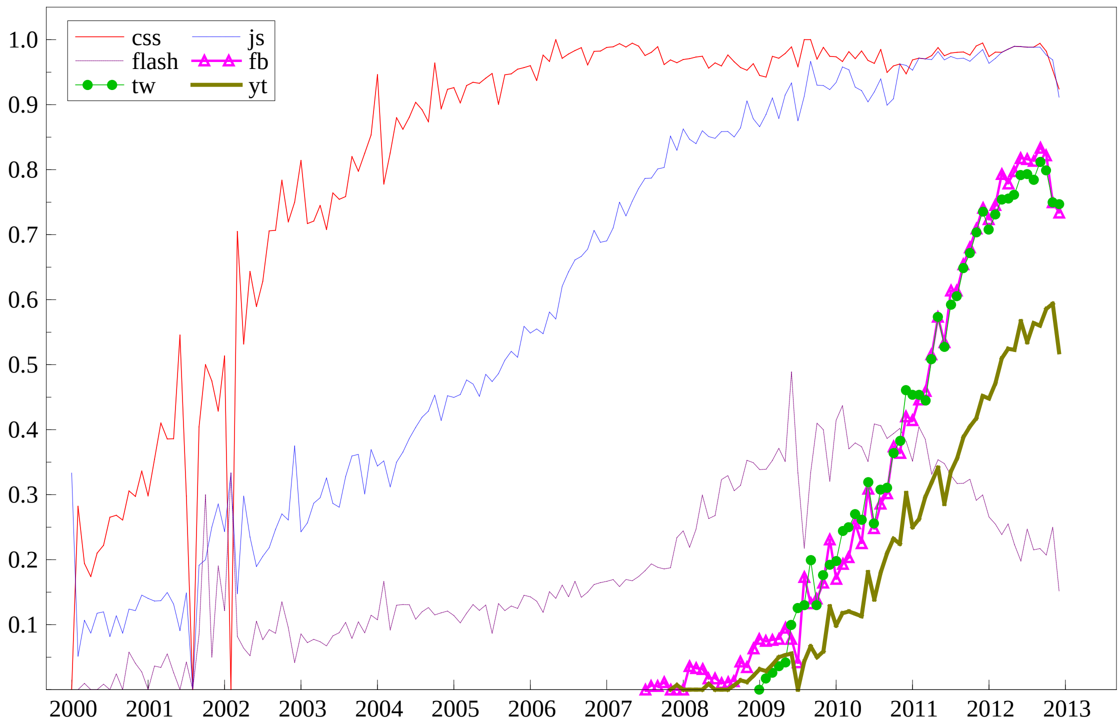

Figure 2: Diffusion patterns for global Sample 2

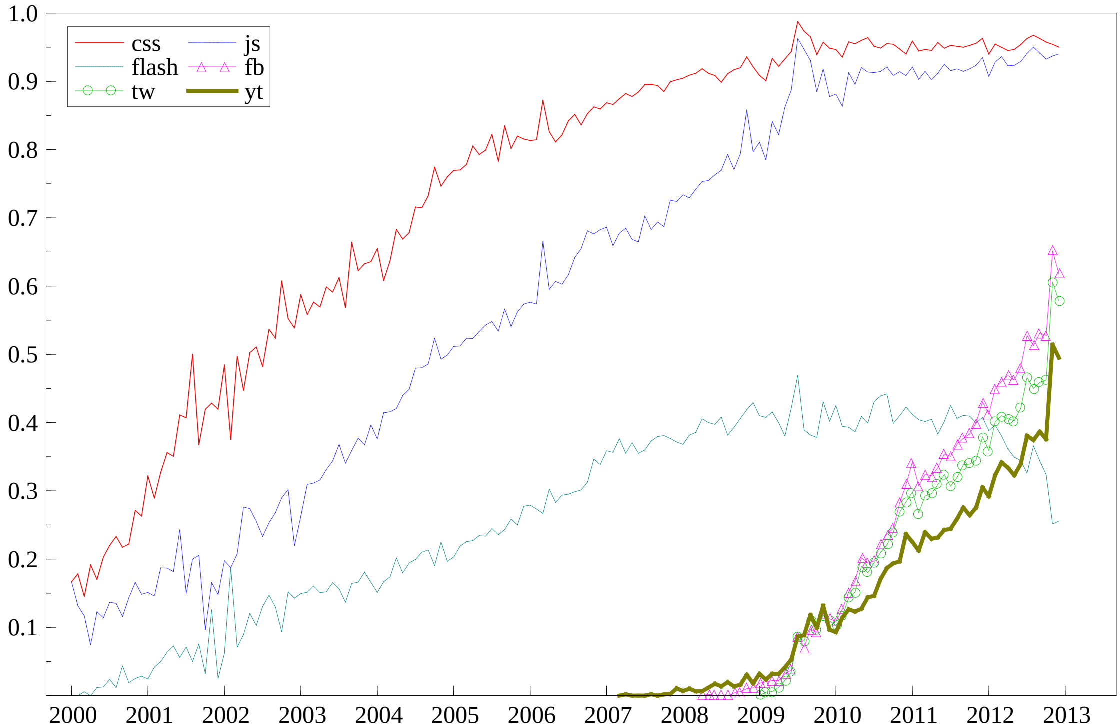

Figure 3: Diffusion patterns for cross sector average of Sample 3

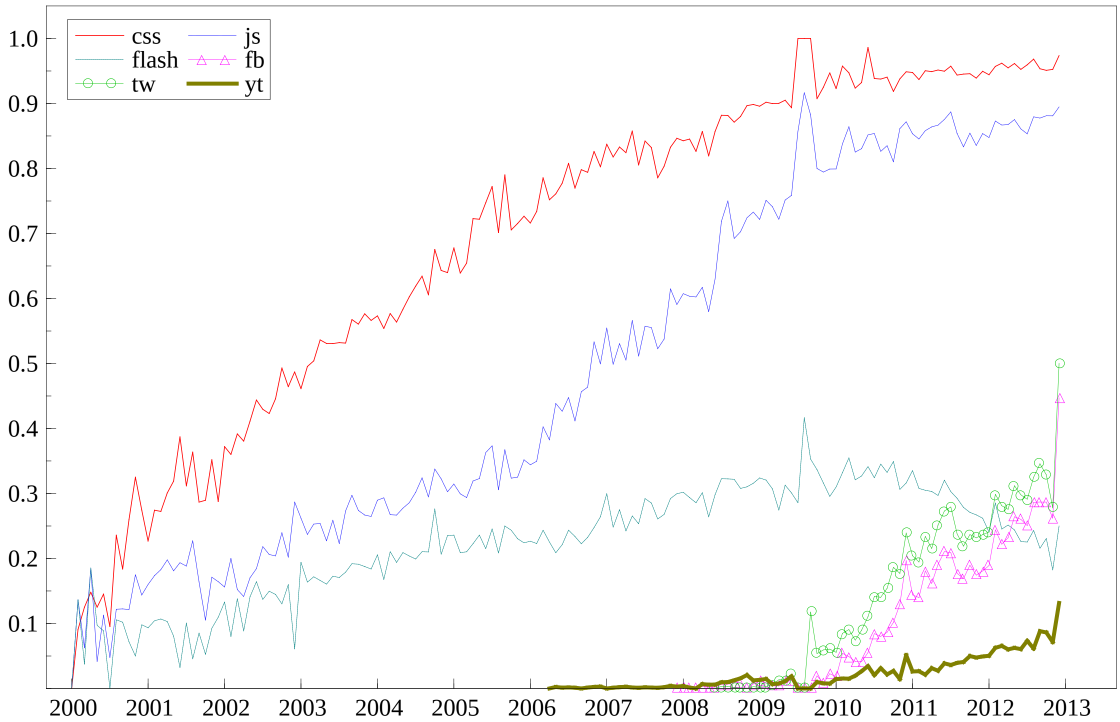

Table 1: A summary of the samples used

Sample	Type	Details	Sites	Data Points
Sample 1	In-depth sector	UK: Higher Education	273	19910 (Average: 72.9/site)
Sample 2	Geographical comparison	Global: Higher Education (Africa, Asia, Australia, Europe, North America, South America)	858	62838 (Average: 73.2/site)
Sample 3	Sector comparison	UK: Advertising and Marketing, Agriculture and Forestry, Construction and Maintenance, Web Design	1454	69451 (Average: 47.8/site)

Table 2: Results for Sample 1, comparing the diffusion of web technologies

Technology	Parameter	Interpretation	Estimate	t-statistic	H_0: equal to CSS (p-value)
Cascading Style Sheets (CSS)	γ	Saturation level	0.9781	132.6000	
	β	Max. speed	0.0740	18.5075	
	τ	Inflection timing	24.0592	34.5363	
JavaScript (JS)	γ	Saturation level	0.9651	4.1887	0.9550
	β	Max. speed	0.0429	2.2282	0.1072
	τ	Inflection timing	67.4690	5.5261	0.0004
Flash (FL)	γ	Saturation level	0.2709	0.6920	
	β	Max. speed	0.0156	0.1750	
	τ	Inflection timing	1.8138	0.0082	
Facebook (FB)	γ	Saturation level	0.2615	0.0264×10^{-9}	
	β	Max. speed	-0.1273	-0.0372×10^{-04}	
	τ	Inflection timing	-0.4681	-0.0157×10^{-10}	
Twitter (TW)	γ	Saturation level	1.2052	0.0428	
	β	Max. speed	0.0105	0.0079	
	τ	Inflection timing	-0.0020	-0.0198×10^{-05}	
YouTube (YT)	γ	Saturation level	2.9732	0.0176×10^{-05}	
	β	Max. speed	-0.0897	-0.0012	
	τ	Inflection timing	-0.3979	-0.0627×10^{-07}	

Table 3: Results for Sample 2, comparing the diffusion of web technologies across a number of geographical regions

	Geography	CSS			JS			FLASH		
Parameter		γ	β	τ	γ	β	τ	γ	β	τ
Estimate	Global	0.9576	0.0438	30.2476	0.9839	0.0346	61.5332	0.3977	0.0518	53.1254
t-statistic		158.5330	31.9448	48.5665	50.1942	18.9563	34.2129	30.0657	7.6734	18.7656
estimate	Africa	0.8847	0.0416	48.3408	0.8888	0.0285	75.4350	0.3597	0.0544	59.0439
t-statistic		40.8557	11.6290	22.0981	8.0689	4.5999	6.5324	18.2803	4.4821	14.0248
H_0: different from global (p-value)		0.0007	0.5463	0.0000	0.3883	0.32896	0.2286	0.0535	0.8281	0.1598
Estimate	Asia	0.9481	0.04520	25.3861	0.9659	0.03175	57.9176	0.4331	0.0617	44.4658
t-statistic		140.0000	25.4068	34.7949	33.0765	12.9639	20.4590	33.7956	6.8835	17.4851
H_0: different from global (p-value)		0.1617	0.4377	0.0000	0.5375	0.2440	0.2015	0.0058	0.2675	0.0007
Estimate	Australia	0.9773	0.0670	21.2806	0.9742	0.0439	54.3303	0.0464	0.0111	-257.049
t-statistic		107.6230	14.8349	22.7285	68.6411	19.9952	42.7905	0.0843	0.0021	-0.0022
H_0: different from global (p-value)		0.0299	0.0000	0.0000	0.4945	0.0000	0.0000	0.5235	0.9939	0.9978
Estimate	Europe	1.0005	0.0351	33.2920	0.8172	0.0303	53.2249	0.2851	0.0456	60.1928
t-statistic		59.9759	14.8018	20.5582	3.9566	2.2497	2.1870	19.6238	5.7622	14.3313
H_0: different from global (p-value)		0.0102	0.0002	0.0601	0.4196	0.7473	0.7328	0.0000	0.4309	0.0924
Estimate	North America	0.9836	0.0421	32.0652	0.9927	0.0214	38.2393	1.8473	-.0068	31.909
t-statistic		83.3865	16.7944	27.1914	2.8787	1.1297	0.3577	0.0523	-0.1942	0.0008
H_0: different from global (p-value)		0.0274	0.4848	0.1232	0.9795	0.4840	0.8275	0.9672	0.0956	0.9903
Estimate	South America	0.8786	0.0504	28.5774	0.8831	0.0287	60.6375	0.5828	0.0469	31.5286
t-statistic		61.4433	11.2708	17.8827	15.3146	6.7632	9.6168	21.9966	4.2078	7.0911
H_0: different from global (p-value)		0.0000	0.1424	0.2960	0.0805	0.1652	0.8870	0.0000	0.6584	0.0000

Table 4: Results for Sample 3, comparing the diffusion of web technologies across a number of industries in the same geographical region

	Sector	CSS			JS			FLASH		
Parameter		γ	β	τ	γ	β	τ	γ	β	τ
Estimate	Advertising & Marketing	0.9279	0.0388	41.3595	0.9786	0.0303	79.3860	0.2775	0.0400	27.6607
t-statistic		52.6872	13.6625	23.3239	22.7578	13.1369	20.0086	16.9284	3.4373	4.7816
H_0: different from Sector4 (p-value)		0.0011	0.6352	0.0000	0.0484	0.2321	0.0938	0.0023	0.0567	0.5031
Estimate	Agriculture & Forestry	0.9534	0.0385	49.1770	2.5802	-0.0094	1.2248	0.2659	0.0338	68.5488
t-statistic		74.1563	22.3713	39.8009	0.0179	-0.0424	0.0001	12.3300	5.4398	9.5419
H_0: different from Sector4 (p-value)		0.0132	0.5470	0.0000	0.9916	0.8671	0.9948	0.0043	0.0000	0.0000
Estimate	Construction & Maintenance	0.9853	0.0349	42.5822	0.5767	0.0554	48.3223	0.3451	0.0343	51.0541
t-statistic		63.9029	18.2528	28.8271	3.5058	0.9201	2.4247	21.7315	7.3295	11.9033
H_0: different from Sector4 (p-value)		0.9973	0.1791	0.0000	0.0031	0.6435	0.2205	0.2679	0.0000	0.0000
Estimate	Web Design	0.9852	0.0374	22.3158	1.0635	0.0275	72.7377	0.3275	0.0622	23.7874
t-statistic		46.9703	8.6670	9.8565	22.1652	12.3868	16.6562	26.0539	3.8875	6.3578

Table 5a: Summary of hypotheses and empirical results

	Sample 1	Sample 2	Sample 3
H1: Web technologies diffuse following an S-shaped pattern.	Yes: CSS, JS	Yes: CSS, JS, Flash	Yes: CSS, and Flash for all sectors, JS for all except A&F
H2: The rate at which web technologies diffuse differs from technology to technology.	Yes: CSS≠JS	Not tested as Sample 2 and 3 were intended to test for differences across regions and sectors, respectively, not across technologies.	
H3: The (level of) critical mass point of the diffusion process of web technologies differs from technology to technology.	No: CSS=JS		

Note: CSS stands for Cascading Style Sheets, JS for JavaScript, Flash for Adobe Flash, and A&F for Agriculture and Forestry.

Table 5b: Summary of hypotheses and empirical results

	CSS	JS	Flash
H4: The rate at which a web technology diffuses is the same from one geographical region to another.	Yes (for max. growth rate): except for Australia's higher, Europe's lower than the global process No (for timing of half-saturation): Africa and Europe slower, Asia and Australia faster than the global process	Yes (for max. growth rate): except for Australia's higher Yes (for timing of half-saturation): except for Australia's earlier adoption	Yes (for max. growth rate) Yes (for timing of half-saturation): except for South America and Asia (faster than the global market)
H5: The (level of) critical mass point of the diffusion process of a web technology is the same from one geographical region to another.	No: Europe and Australia and North America higher, Africa and South America lower	Yes, except for South America (lower)	No: lower for Europe and Africa and higher for Asia and South America
H6: The rate at which a web technology diffuses is the same from one industry to another.	Yes (for max. growth rate) No (for timing of half-saturation): A&M, A&F, C&M slower than WD	Yes (for max. growth rate) Yes (for timing of half-saturation)	No (for max. growth rate): A&M, A&F, C&M lower than WD No (for timing of half-saturation): A&F and C&M slower than WD
H7: The (level of) critical mass point of the diffusion process of a web technology is the same from one industry to	No: A&M and A&F lower saturation levels than WD	No: A&M and C&M lower than WD	No: A&M and A&F lower than WD

another.			

Note: CSS stands for Cascading Style Sheets, JS for JavaScript, Flash for Adobe Flash, A&M for Advertising and Marketing, A&F for Agriculture and Forestry, C&M for Construction and Maintenance, and WD for Web Design. As discussed in section 3.3., both the maximum growth rate ($\beta/2$) and the timing of half saturation (τ) are used to make inferences about the critical mass point.